A Low illumination image Enhancement Algorithm Based on Morphological-Retinex (MR) Operator

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***Abstract*—Low-illumination images often appear in night environments, which is lack contrast and sharpness. Night image recognition, capture, or autonomous-driving systems require meritorious algorithms to process low-light images taken. The Retinex-based method has been used in image enhancement universally, but previous literature has some limitations for enhancement, but robustness is poor and only valid for some pictures. Because of those weaknesses, the night recognition and low-light image training programs are prone to fail. To solve those problems, we propose a new algorithm called Morphology-Retinex (MR). Introduce morphology to strengthen the details and edges of the picture. Use the new automatic color restoration method to restore the authentic color of the object in pictures. As a result, the scores of PNSR and SSIM are 15% higher than traditional methods, and the clarity is excellent, which is about 50% higher than similar algorithms in recent years. This algorithm can improve the quality of low-illuminance image data sets and reduce the difficulty of image recognition. And it will increase the success rate of training machine learning models using night image data sets.**

Index Terms*—— Retinex; Mathematical Morphology; Low-light image enhancement; Color restoration;

I. INTRODUCTION

Modern computer vision and digital image processing applications require images to have a high degree of visibility in order to correctly complete the specified tasks. Especially in the field of computer vision and digital image processing, images with high visibility can be used to complete model training through machine learning to correctly finish each designated task. Operations such as text recognition, image segmentation, and color recognition all need the image to be sufficiently clear in terms of color, sharpness, and edges so that it can facilitate region extraction.

Retinex is a compound word its composition is retina+ cortex. Read literally, this method is established like the human retina. This model was proposed by Land and McCann (Fig 1). Based on this model, a variety of image enhancement algorithms have been proposed. The classic algorithms include MSR (Multi-Scale Retinex) [2], MSR with color restoration (MSRCR)[3], and with automatic color restoration (AMSCR) [4]. These algorithms have strong robustness, have been widely used in many fields. However, these algorithms may cause images more distorted and lose more details. In recent years, new algorithms have been proposed to improve their effects.

For instance, Xu Jun uses the extracted structure and texture map to regularize the illumination and reflection components, thereby improving the overall illumination effect of the picture [5][6]. Zou Muchun proposed an image color estimation method based on white, gray, and black block supervision to improve color saturation [7]. Their methods are similar to the original image in terms of color distribution and similarity, avoiding excessive distortion. However, these algorithms have not effectively improved the sharpness of the image, the gray value of the image and the Laplacian gradient score is not ideal. The unsatisfactory clarity of the image data set will lead to difficulty in improving the success rate of model training.

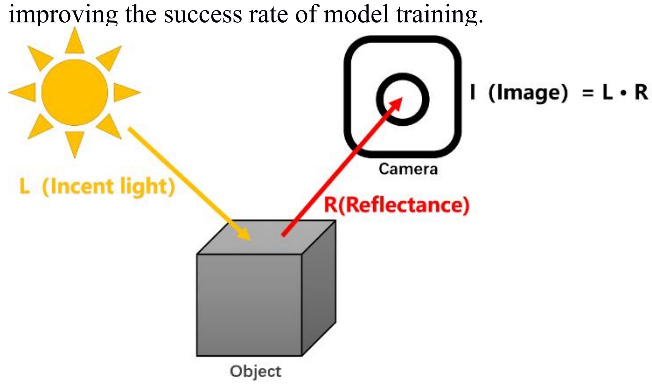

Fig. 1 Retinex module [1]

In this study, to improve the limitations discussed above. We propose a new algorithm for low-illumination enhancement based on the mathematical morphology and Retinex-based method. Morphological operators are used to modifying or describing the shape of objects and be defined as a measure for the analysis of spatial structures [8]. Based on the Retinex module decomposes a picture into illumination and reflection, setting our detail result as Gain, which will be put in the reflection part. Preventing excessive enhancement is necessary. Then we define a constant as limit parameters, afterward applying a color restoration, which using Max-Min Normalized thought. Based on those measures, the photos have been sharped obviously, meanwhile, the color also has been adjusted into a relatively ideal result. Finally, use the gamma correction function to modify color richness its measurement parameter named γ. Changing the constants, which are like, etc. can alter the strength of enhancement a limited range is provided to prevent over-enhanced or image noise phenomenon. The flow chart of the algorithm is shown below Fig 2.

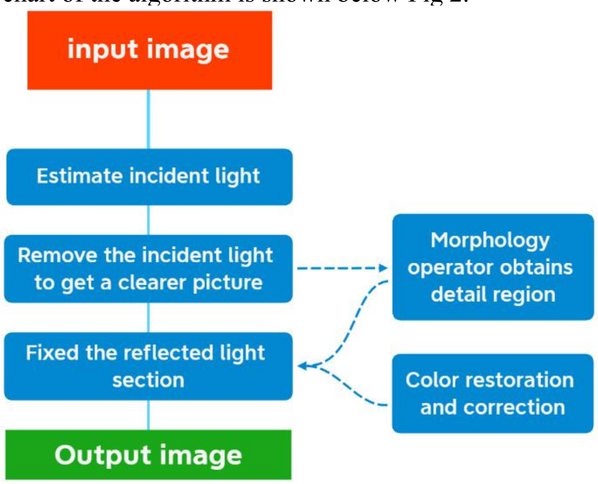

Fig. 2 Flow chart

As a result, we test dozens of low-light pictures and compare them with recent literature (between 2019 and 2021) and traditional algorithms (classical Retinex modules). The result shows that on SSIM (Structural Similarity) and PNSR (Peak Signal-to-Noise Ratio) our score is higher 17% than traditional methods. This algorithm has the best score in clarity index like SMD (Sum modulus difference) and Laplacian gradient. The comprehensive information will be demonstrated later.

The rest of this paper is organized as follows: related work is introduced in Section Ⅱ. While Section Ⅲ describes the detail of the algorithm. The result and comparisons along with their discussions are stated in Section Ⅳ. In the end, the conclusion of this article is in Section Ⅴ.

II. RELATED WORK

A. Retinex module in low-light image

After NASA (National Aeronautics and Space Administration) declared that they use the Retinex algorithm in space photo enhancement [9], it starts to become famous and popular in the image field.

The space photo has a lot of similarities with low-light images. The low-light image's sight shows poor quality due to their big grayscale value. Using Retinex to estimate and remove illumination is a traditional measure to resume value into normal-light range. To avoid distortion, they deem MSR can maintain the image's fidelity and in range of dynamic. The calculation formula is as follows:

$$\log(I) = \log(L\cdot R)\ \#(1)$$

Firstly, take the logarithm of both sides of the equation. Regard R as our objection r, so the formula will be changed as an additive form (2)

$$r = \log(R) = \log(I) - \log(L)\#(2)$$

Now we need to estimate L use Center wrap function, F as our function. The F satisfy formula (3), specify c as the gaussian wrap scale, λ as a scale.

$$\iint F(x,y)\,dxdy = 1\ \#(3)$$

$$F(x,y) = \lambda * e^{-\left(\frac{x^2+y^2}{c^2}\right)}\ \#(4)$$

Make L=F·I, consequently, (2) will be transformed into (5).

$$r = \log(R) = \log(I) - \log(F\cdot I)\ \#(5)$$

After illumination removing, the visibility of low-light image is improved. Based on (5), MSR set different c to solve r, normally set 3. This is because a single scale is prone to cause a huge loss of image. The equation changed as follows:

$$\begin{cases} r = \sum_{i}^{K} w_i(\log(I) - \log(F_i\cdot I)) \\ \sum wi = 1 \end{cases}\ \#(6)\ \#\#$$

This method in some details will lead to color distortion and lack of sharpness in the edge. Further research tried many ways to improve those demerits.

For instance, Lin H's team proposed many methods in the night or low-light image enhancement based on MSR [10] [11]. They mainly offer restrictive parameters to the module like L1 norm, augmented Lagrange multiplier, etc. to increase the robustness of the Retinex module. Their algorithm's formula is:

$$I = L\cdot R + N\ \#(7)$$

N means the noise term. Then they use their methods to estimate N and remove it as a denoise operation to recover the images. Jun Xu's team utilizes a way called "exponentiated local derivatives" to generate its structure map and texture map, and through the map to modify the value of L and R. Their result highly improved the quality of images in SSIM and PSNR the score is closing to normal picture.

However, both of them and MSR, MSRCR, etc. apply the overall enhancement method, the reflectance component is prone to be over-smooth because of filter operation. So that picture's clarity and details will be undermined and difficult to utilize in model training.

B.Morphology

Mathematical Morphology was developed in 1964 by the collaborative work of Georges Matheron and Jean Serra, has many basic operators. If the color of the image is bright enough those operators can be used in the image analysis. Let's illustrate some of them we used.

a. Dilation & Erosion

The dilation of R by element S is defined by $R \oplus S$, The dilation is commutative, also given by $S \oplus R$. erosion defined by $R \ominus S$ or $S \ominus R$ the specify algorithm is equal to use the transposed structuring element in Minkowski subtraction (Erosion) and Minkowski addition (Dilation) as (9).

$$\begin{cases} R \oplus S = \{r + s \mid r \in R, s \in S\} = \bigcup_{s \in S} Rs \\ R \ominus S = \{r \mid \forall s \in S: r - s \in R\} = \bigcap_{s \in S} Rs \end{cases} \#(9)$$

b. opening & closing

Opening and closing is the combination of dilation and erosion, opening ($R \circ S$) is an erosion followed by a Minkowski addition with the same structuring element. On the other hand, closing ($R \cdot S$) is a dilation followed by a Minkowski subtraction with the same structuring element. They can be used in contacting objects that are separated by noise or gaps. Closing will remove indentations and smooth boundary of the object. Their formulas are written as follows:

$$\begin{cases} R \circ S = (R \ominus S) \oplus S \\ R \cdot S = (R \oplus S) \ominus S \end{cases} \#(10)$$

c. white top-hat & black top-hat

Top-hat transform is an operation to extract details from the original pictures. There are two different transforms, the white top-hat transform is defined by the origin image minus the opening result. It can highlight areas where is brighter than the area around the outline of the original object. While the black top-hat transform is defined as the difference of image and closing result. It can separate patches that are brighter than neighboring ones. Therefore, through multiple iterations of them to accomplish the task of feature extraction, background equalization, etc. [13] Basic formula follows:

$$\begin{cases} T_{white}(I) = I - I \circ b \\ T_{black}(I) = I - I \cdot b \end{cases} \#(11)$$

III. METHOD

The main purpose of the algorithm is to improve the brightness and contrast of low-illumination images, which also ensures the clarity of images. Preserving features and edge details while improving overall color visibility. Make the output picture adapt to the perception of human eyes and facilitate the related training of machine vision.

To protect more features and detail, we use the Retinex-based method based on (2). After the logarithmic parameter is obtained, the color can be adjusted initially by converting it to a normal value. (12) is the step to adjust the pixel distribution.

$$\begin{cases} mmin = min(r), mmax = max(r) \\ I = \dfrac{r - mmin}{mmax - mmin} * 255 \end{cases} \#(12)$$

Where mmin means the minimum value of r, and mmax is to gain the maximum of r. The thought of recovery is Max-Min normalization. The gray value of the picture at this time is controlled in the middle range, which can facilitate the subsequent stretching operation of each pixel.

When calculating our detail gain in two parts, the algorithm chooses μ to mastery the intensity of enhancement. Morphological open-cap and closed-cap operations were used for the previous results, and the two parts obtained were used to perform regional sharpening on the near edge and the far edge of the image respectively. The part of the original image is the edge detail of the entire image. Besides, the internal color of the close end details of the open operation is also incorporated to enhance the clarity of the close end. The calculation formula is as follows:

$$I_{st} = \mu(T_{white}(I) - T_{black}(I)) \#(13)$$

Where $T_{white}(I)$ mainly keeps the proximal image detail $T_{black}(I)$ Image contours at the far end. After summing, the details of the entire image are extracted.

The abridged pseudo-code is provided below:

Algorithm 1: Solve reflectance and detail

Input: raw image I, parameters μ, iteration array K
Initialization:
for (i = 1, …, K) do:
1. Update r by Eqn. (6)
2. Update I by Eqn. (12)
   If (i = K):
      Solve I_{st} by Eqn. (13)
   End if
End for
Output: reflectance R and strength detail I_{st}

The array K means K different scales are used. From the experimental result selecting 15,80,250 as an array and setting μ=0.10 to solve the module is acceptable. Algorithm 1's output as Fig 3.

(a) (b) (c)

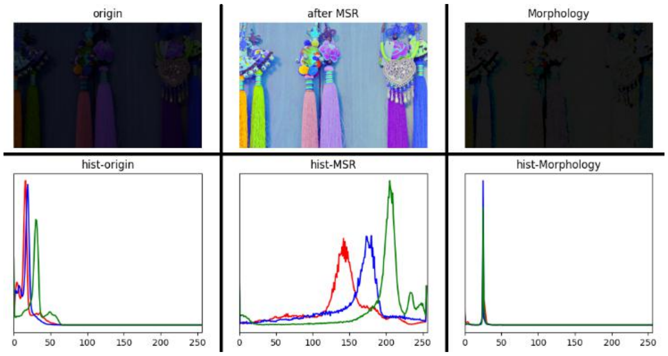

Fig. 3 Comparison with original picture (a)-Original picture and its histogram (b)-R and its histogram (c)- I_{st} and its histogram

MSR calculates the image without illumination. (c) obtains many slight edges and detailed information. Merge (b) and (c) in superposition can solve the problem of edge blur. The following formula will solve details-enhanced reflectance.

$$R_{de}(x,y) = R(x,y) + I_{st}(x,y) \quad (13)$$

Color restoration modify R_{de} to get better contrast and color richness. R_{de} has some murky area and unsaturated color pixel dots. Consequently, the following action will let it enhance automatically like AMSRCR, set coefficient α = 125 to control gray value distribution interval. which is close to the center of 0 to 255, use raw picture multiply by α and subtract the sum of the original 3-channel values as a recovery coefficient array. Based on learning from the idea of standardization, our second step is to normalize those values, and we give the color restore steps as follows:

$$\begin{cases} R_{co}' = \left(\log(\alpha \cdot I) - \log\left(\sum_{i=1}^{3} I_i\right)\right) \cdot R_{de} \\ R_{co} = \dfrac{R_{co}' - min(R_{co}')}{max(R_{co}') - min(R_{co}')} \end{cases} \quad (14)$$

In order to solve the problem of color distortion in the region, Gamma correction is used to correct the color of the reflected light. This is a nonlinear operation used to encode and decode brightness in video or static image systems [14]. It is a nonlinear operation of the gray value of the input image, which makes the gray value of the output image and the gray value of the input image have an exponential relationship. Equation is:

$$I_{out}(x,y) = \left(\left(\frac{I_{in}(x,y)}{255}\right)^{\gamma}\right) \cdot 255 \quad (15)$$

Visually speaking $\gamma < 1$ makes dark regions lighter. On the opposite, when $\gamma > 1$ the shadows will be darker, γ=1 is equal to the input image. The effect when γ=0.25, 0.5, 2,3 follows in Fig 4.

Fig. 4 Gamma correction result in different γ

Based on the results in Figure 4, select γ=2 to correct the image. Algorithm 1 changes the reflected light and the detail part, and the gray value of the low-illumination image is generally low. Since most screens have a γ value set at 2.2, γ=2 balances the grayscale value and keeps the result in the best light range. In addition, the gamma correction may produce an illegal grayscale value greater than 255 or less than 0, which is corrected with (16).

$$\begin{cases} I_{out}(x,y) = \min(255, I_{out}(x,y)) \\ I_{out}(x,y) = \max(0, I_{out}(x,y)) \end{cases} \quad (16)$$

Algorithm 2: Color restoration and correction

Input: raw image I, parameters γ, α

Initialization: estimate R_{de} by algorithm 1 and (13)

1. Get R_{co} by making color restoration by (14)
2. Apply gamma correction (15) to R_{co}
3. Modify R_{co} using equation (16)

Output: final output image I_{out}

Algorithm 2 needs to input details and reflected light, continue to adjust the reflected light, and then integrate the results.

The following is the histogram between the output of algorithm 2 and the original image in Figure 5. The histogram distribution of algorithm 1 is inclined to the left region, and the picture is slightly white. The cyclic correction of algorithm 2 is closer to the visual habit of human eyes.

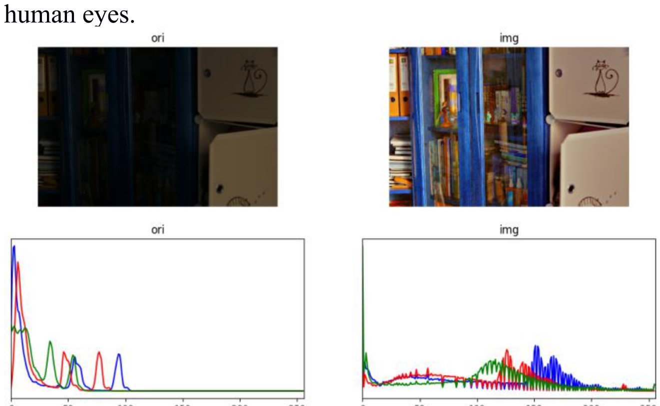

Fig. 5 Raw image(left) and Our Result(right) with their histogram (second line)

The distribution of image types in the low-light image database is very wide. In order to test the generalization ability of data processing, the low-light and foggy image enhancement effect was also tested. Our method, without specific defogging algorithms, can effectively remove the slight haze in the image.

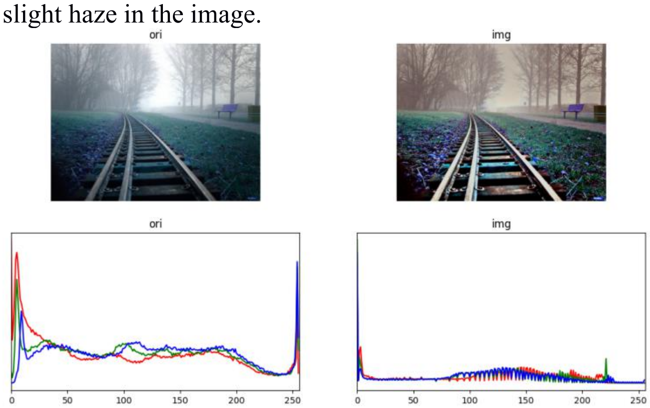

Fig. 6 Low-light with Foggy input(left) and output(right) and their histogram (second line)

In Figure 6, our results are better enhanced than those of MSRCR and AMSRCR, and the details of the railway tracks are clear and colorful. The increase in clarity is conducive to machine learning.

IV. EXPERIMENTS AND RESULT

In this section, we evaluate the quality of the proposed Morphological-Retinex (MR). Compared with the recent year's algorithm in Retinex and low-light enhancement methods, the Illumination Boost Algorithm (IBA) is purposed in 2019, they focus on illumination part boost. And Structure and Texture Aware Retinex Model (STAR) also attempts to improve MSR's effect. All those experiments are run on a Dell Inspiron 3476 with Intel(R) Core (TM) i5-8250U CPU and 8GB RAM in Windows 10.

A. Quality Evaluation Index

SSIM (structural similarity) and PNSR (peak signal-to-noise ratio) were selected as distortion indexes. SSIM is widely used in image perception quality research, Wang, Zhou; Bovik published it in 2004 [15]. The closer the value is to 1, the better the similarity. From testing about 20 images, our method obtained a high score in most photos.

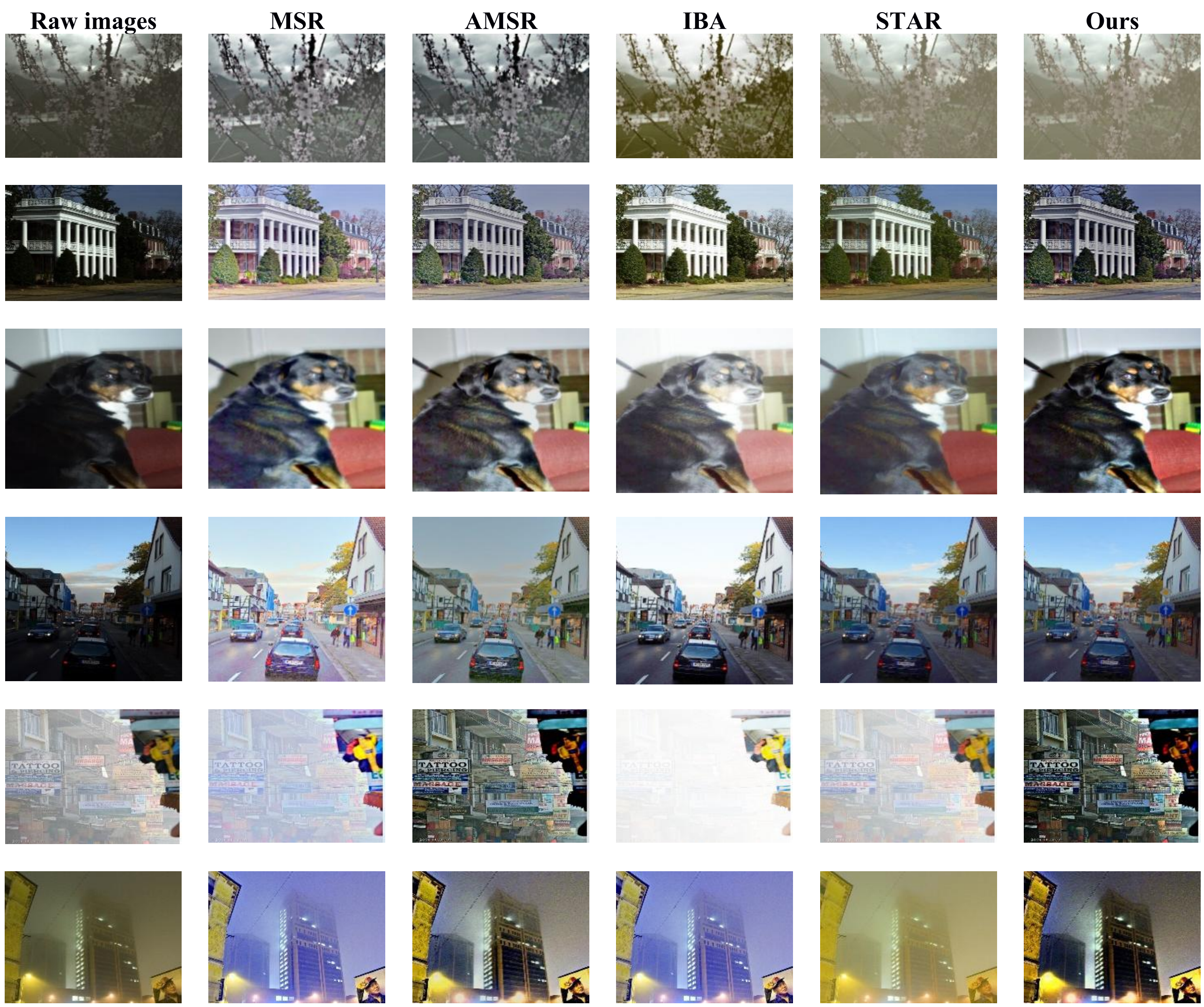

Fig. 7 The comparison with others boosted methods: 1: the original images (getting from [5][6][11][12][16], top to bottom flower, building, dog, street, neighborhood, night) 2. MSR[1] 3.AMSRCR[4] 4.IBA[6] 5. STAR[5] 6.ours(MOR)

TABLE 3 SMD Result

SMD	flower	building	dog	street	neighbor	night
MSR	2896269	**22615966**	1265005	**4663683**	2811327	4120334
AMSR	2931111	21023761	1282955	3782103	8636260	7055907
IBA	2660879	20049338	890066	4683235	1005808	1659905
STAR	1174322	13636582	612829	3387138	2544749	1828903
Ours	**3019361**	20887868	**1320666**	3721785	**9310951**	**7440631**

TABLE 1 The SSIM Result of Fig. 8(UNIT:DB)

	msr	amsr	iba	STAR	ours
flower	0.72	0.74	0.71	**0.81**	0.76
building	0.41	0.48	0.41	**0.6**	**0.6**
dog	0.55	0.54	0.48	0.66	**0.67**
street	0.46	0.53	0.51	**0.65**	0.6
neighbor	**0.9**	0.61	0.58	0.89	0.47
night	0.83	0.61	0.68	**0.86**	0.55

In Figure 7, our result of Neighbor and Night are significantly clearer than other algorithms. But the score of SSIM is not as high as STAR or MSR. This phenomenon is due to the poor quality of the reference image itself. SSIM mainly calculates the similarity between the image and the original image. A high similarity does not indicate good processing quality, which means that although other algorithms score high, the image is still difficult to be recognized and trained.

PSNR is a description of the loss of image compression. A high value means a small loss. However, the sensitivity of human eyes may be affected by many factors, and the evaluation result of PSNR may be somewhat different from that of human eyes. Table 2 is the mean value of PSNR of 17 low-light images in different types.

TABLE 2 Average PSNR

	MSR	AMSR	IBA	STAR	Ours
PSNR	7.95	10.88	9.36	14.36	12.99

The algorithm (MR) also obtains an acceptable PSNR with a fraction distribution similar to that of SSIM, with a lower fraction in the low-illumination fog map. Similarly, SSIM and PSNR can't reflect the true quality of the picture. Additional metrics need to be used to evaluate the image.

B. Clarity Evaluation Index

The clarity index selected below are the evaluation methods for non-reference images, which can overcome the uncertainty of the original image itself. That is, SMD (Sum modulus difference), Laplace gradient, etc., to represent the image clarity.

When the camera lens is entirely focused, the picture is the clearest while the grayscale value is the highest. Therefore, SMD can be used as the basis for focusing evaluation. Laplacian Gradient uses its operator to extract gradient values in horizontal and vertical directions respectively to display image information richness. Comentropy and entropy also represent the richness of image information. The larger the values they satisfy, the clearer the picture. The results of Fig.7 are shown in Table 3. And Table 4 shows all scores of different clarity index with all pictures we used.

TABLE 4 Result In Average Of Different Index

	SMD	Lap.	Entropy	Comentropy
MSR	6094939	2967	4.98	7.44
AMSR	6975684	2967	5.08	7.41
IBA	4655421	1664	4.80	6.52
STAR	3609656	997	4.76	7.24
Ours	7168638	3145	5.16	7.41

From Table 3 and 4, both IBA and stars have a great loss of clarity, especially in "neighbor", and the effect is even worse than the traditional method. This is mainly because the filtering operation in their model undermines many details, causing some edges to be more blur, which is difficult to extract or segment in image recognition.

The output of our algorithm can judge the color by human eyes. Besides, the clarity is significantly improved, which will facilitate data training based on the existing low-light image database.

V. CONCLUSION

In this paper, we incur morphological operator and color correction in the Retinex algorithm to solve the problem in low-light image enhancement. This method can deal with ordinary low-illumination images, and its robustness is stronger than the current algorithms. It can be used for cleaning low-illumination image database by dropping illumination fog images. Improve the success rate of night machine vision model training.

The current algorithm completely deletes the incident light of low-illumination images, and many current algorithms like ZoHair [6] retain part of the incident light. In the future, we will explore using incident light as a reference to retain more of the image content or develop a night recognition system based on this algorithm.

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